LOCATING AUTOMATED EXTERNAL DEFIBRILLATOR ENABLED MEDICAL DRONES TO REDUCE RESPONSE TIMES TO OUT-OF-HOSPITAL CARDIAC ARRESTS

by

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STATEMENT OF THESIS APPROVAL

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ABSTRACT

Out-of-hospital cardiac arrest (OOHCA) is prevalent in the United States. Each year several hundred thousand people die due to cardiac arrest. The automated external defibrillator (AED) has greatly enhanced survival rates for OOHCA. However, one of the most important factors in successful resuscitation is emergency medical services (EMS) response time. Unmanned aerial vehicles, or drones as they are more commonly called, have routinely been used for remote sensing but there are new opportunities to use drones for medical emergencies due to their high speeds and ease of navigation. While a drone with an on-board AED could potentially reduce response times to OOHCAs, it remains unclear how effective it is compared to ground EMS. It also remains uncertain how a network of AED-enabled drones should be implemented so that it can best serve cardiac arrest patients.

This study examines historical out-of-hospital cardiac arrests and develops a new location model, referred to as the *backup coverage location problem with complementary coverage* (BCLP-CC), to aid in the deployment of a network of AED-enabled medical drones. By explicitly considering overlapping and partial coverage, the BCLP-CC optimally places drones and the corresponding launch sites while significantly improving backup coverage. Results show that 90.4 percent of historical out-of-hospital cardiac arrests in Salt Lake County can be responded to within one minute by using seventy-one drones and sixty-eight launch sites. In addition, 58.9 percent of incidents are covered two

or more times, a significant improvement over existing models.

The BCLP-CC was then extended to the *backup coverage location problem with complementary coverage and capital improvement* (BCLP-CCCI) to minimize implementation costs. Analyses results of the BCLP-CCCI show that by upgrading forty-four existing EMS facilities, by building twenty-six new launch sites, and by using seventy-six drones, 90 percent of the historical incidents could be reached by at least one AED-enabled drone within one minute, 65 percent of the demand could be reached by a secondary drone within one minute, and implementation costs could be reduced by 17 percent as compared to the results of the BCLP-CC.

Although there are many concerns and limitations associated with medical drones, this study shows that an optimized network of drones has the potential to significantly reduce live-saving equipment travel times.

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CHAPTER 1

INTRODUCTION

Sudden cardiac arrest (SCA) has been defined in a set of guidelines released in 2006 by the American College of Cardiology Foundation (ACC), American Heart Association (AHA), and European Society of Cardiology (ESC) as “an unexpected circulatory arrest, usually due to a cardiac arrhythmia occurring within an hour of the onset of symptoms, in whom medical intervention (e.g., defibrillation) reverses the event” (Heart et al. 2006, 755). The guidelines also define sudden cardiac death (SCD) as “Death from an unexpected circulatory arrest, usually due to a cardiac arrhythmia occurring within an hour of the onset of symptoms” (Heart et al. 2006, 755). SCA and subsequent SCD are quite prevalent in the United States. Despite various definitions of SCD and SCA among studies, it is estimated that between 180,000 and 450,000 cases of SCD are reported each year (Kong et al. 2011). The majority of SCA incidents involve patients with no history of heart problems; cardiac arrest may be the first indication that the patient in suffering from cardiovascular disease. This makes prevention difficult and as a result only 1-5 percent of all cardiac arrest patients are successfully discharged from the hospital (Becker et al. 1991; Cummins et al. 1991; Caffrey et al. 2002; Galea et al. 2007). While research continues in cardiovascular disease, much attention has been paid to improving prehospital care.

One of the deciding factors in patient survival from a cardiac arrest event is response time. Multiple studies have shown that reducing response times by just one minute can significantly improve the odds of survival (De Maio et al. 2003; O'Keeffe et al. 2010).

Recent advancements in medicine and technology have given rise to the medical drone, an autonomous aerial vehicle with the capability to quickly deploy, travel at high speeds, and carry medical equipment to emergency situations (Husten 2014; Webredactie Communcation 2014). Since the medical drone does not rely on road networks, can avoid traffic, and can possibly be dispatched quicker than a ground ambulance, it provides the capacity to significantly improve response times for medical emergencies. In 2014, Alec Momont announced a prototype AED-enabled medical drone (Communication 2014). This specific drone has several unique capabilities including an on-board AED, a direct connection to the emergency dispatcher, live video, and speeds up to 100 km/h.

While the AED-enabled drone could potentially enhance response time to OOHCAs, it remains unclear how effective it is compared to ground EMS and how to strategically implement a network of AED-enabled drones that can best serve cardiac arrest patients. This study examines historical out-of-hospital cardiac arrests and develops new location models to establish a cost-effective system of AED-enabled drones that has the potential to significantly reduce EMS response times for future cardiac arrest incidents. Specifically, by analysing empirical medical data, applying machine learning techniques, and by using spatial optimization methods, this study addresses the following research questions:

(1) What are the current response times to cardiac arrest incidents in Salt Lake County?

(2) What are the most important factors contributing to SCA survival rates in Salt Lake

County?

(3) Can a network of AED-enabled drones significantly reduce travel time delays when responding to cardiac arrest incidents in Salt Lake County?

(4) What is the best way to implement a cost-effective network of medical drones in Salt Lake County?

The research is organized as follows. Chapter 2 starts with a review of sudden cardiac arrest, medical drones, and spatial optimization as it pertains to emergency medical services. Chapter 3 focuses on the study area and examines the empirical medical data in detail. Chapter 4 outlines the methods used in this study. First, the factors that contribute to SCA survival rates are examined using random forests to determine the importance of EMS travel time. Next, the methodology behind the facility locations and service areas is explained. The *backup coverage location problem with complementary coverage* (BCLP-CC) and the *backup coverage location problem with complementary coverage and capital improvement* (BCLP-CCCI) are then formulated to find the optimal configuration of AED enabled drones. The results of this study are compiled in Chapter 5. Finally, Chapter 6 summarizes the results of this thesis, addresses the limitations of this study, and identifies methods that could be used in the future to enhance this research.

CHAPTER 2

LITERATURE REVIEW

2.1 Factors Contributing to SCA Survival Rates

There are many factors that affect a patient's chance of survival from out-of-hospital cardiac arrest (OOHCA). A study in Sweden identified the six most important: (1) initial heart rhythm, (2) location of arrest, (3) witnessed status, (4) bystander cardiopulmonary resuscitation (CPR), (5) patient age, and (6) rescue team response time (Herlitz et al. 2005). Among these six components, all except for the patients age, can be used in conjunction with new technologies to increase survival rates.

Ventricular fibrillation (VF), ventricular tachycardia (VT), and asystole are the three most common heart rhythms encountered (de Vreede-Swagemakers et al. 1997; De Maio et al. 2003). Rapid heart rhythms such as VT and VF have been associated with better prognosis. One of the reasons for this is that VT and VF are rhythms that can be detected and changed by automated external defibrillators (AED). The AED is a device that was developed to automatically monitor a person's heart rhythms and, if necessary, provide electric shocks to reestablish a productive heart rhythm. By including built-in instructions and voice commands, almost any bystander can successfully use an AED. Several studies have shown that AED use can drastically increase the survival to discharge rates for SCA (Cummins et al. 1984; Marenco et al. 2001; Caffrey et al. 2002).

It has been well established that the majority of OOHCAs occur at the patient place of residence (de Vreede-Swagemakers et al. 1997; Straus et al. 2004; Galea et al. 2007). Between 70 and 80 percent is the generally accepted range of cardiac arrests that occur at home. This leaves 20-30 percent of cardiac arrests occurring outside of the home in public places. It has been shown that patients whose cardiac arrest event was witnessed by a bystander or emergency medical service (EMS) crews have higher survival to discharge rates. It has also been discovered that up to 54 percent of sudden cardiac arrests (SCA) occurring at home and 84 percent of SCAs occurring outside the home are witnessed (de Vreede-Swagemakers et al. 1997). It has been shown that witness rates vary among races (Cowie et al. 1993). In the de Vreede-Sagemakers study, only one victim, out of 176, survived an unwitnessed SCA giving a survival rate of 0.6 percent. Survival rates of witnessed SCA were 7.7 percent. Having someone recognize the symptoms of SCA allows EMS to be called on scene, potentially reduces delay in response times, and potentially allows for bystander CPR which could increase the chances of survival (Lund and Skulberg 1976; Cummins et al. 1985; Einarsson, Jakobsson, and Sigurdsson 1989)

It is well known that age significantly affects cardiac arrest incidence rates and mortality rates. The incidence of coronary disease and sudden cardiac death (SCD) was shown to increase significantly between the ages of forty-five and sixty-four (Kannel and Thomas 1982). This study also showed that women lag behind men in incidence by twenty years. Another study showed that incidence of cardiac arrest increased at a linear rate for both men and women as age increases (Becker et al. 1993). White men aged thirty-two to thirty-six had an incidence rate of around 65 per 100,000 persons while white men aged seventy-seven to eighty-one had an incidence rate near 900 per 100,000 persons. Similar data points exist for black males, white females, and black females. Although focused on racial discrepancies, Galea et al. (2007) found that age groups 65-74, 75-84, and greater than 85 contributed to nearly 70 percent of the OOHCA patients in the 2002-2003 study.

Although the previous factors are important, one of the key variables in cardiac arrest survival is time of victim discovery to application of meaningful shock therapy via AED. A study performed in the United Kingdom estimated that reducing overall response times by one minute improved the odds of survival by 24 percent with 95 percent confidence intervals of 4 percent and 48 percent (O'Keeffe et al. 2010). Another study performed in Canada found a sharp decline in survival during the first five minutes after a cardiac arrest (De Maio et al. 2003). For each minute of delay, the odds of survival decreased by 23%. Therefore, by developing systems using new technologies, such as drones, that significantly reduce the time between cardiac arrest onset and essential shock therapy, cardiac survival rates may notably improve.

2.2 Medical Drones

Unmanned aerial vehicles (UAVs) have routinely been used for remote sensing, aerial imagery collection, and military purposes (Everaerts 2008). UAVs may soon be used to transport goods quickly, safely, efficiently to both accessible and inaccessible terrain (Thiels et al. 2015; Federal Aviation Adminstration [FAA] 2016). Using UAVs or drones for medical purposes has only recently been seriously considered. A recent article discusses how drones can potentially be used to transport medical supplies such as blood derivatives and pharmaceuticals to hospitals, remote areas, and mass causality incidents (Thiels et al. 2015).

In addition to transporting medical supplies, drones may have the ability to provide other medical treatments such as shock therapy via an AED. AED-enabled medical drones are designed to be deployed by emergency dispatchers at a moment's notice and fly to the patient using the caller's cell phone Global Positioning System (GPS) receiver as the target. Upon reaching the target, the dispatcher, through real-time video, can instruct the caller to use the AED on the patient. A brief outline of a cardiac event where a drone is deployed is outlined below:

1. The patient begins experiencing a cardiac arrest.
2. A bystander or the patient calls the emergency hotline (911) for help.
    a. Bystander may perform CPR on the patient.
3. Emergency operators/dispatchers notify local EMS agency/station.
4. Emergency operators/dispatchers deploy medical drone to patient (using cell phone GPS as the target).
5. The medical drone flies to the patient and lands.
6. The bystander obtains the medical drone and brings it to the patient.
7. The bystander begins using the AED on the patient.
8. EMS personnel arrive on scene and provide medical care.
9. The medical drone is repackaged and it flies back to its launch site.

Drones can be outfitted with a multitude of sensors, cameras, and on-board microprocessors to autonomously self-stabilize, follow paths, and detect and avoid obstacles (Jimenez Lugo and Zell 2013). Computer vision and machine learning algorithms have been developed and experimentally tested to successfully navigate drones in narrow environments and in areas where GPS signals are nonexistent (Krajnik et al. 2012; Jimenez

Lugo and Zell 2013; Mercado, Castillo, and Lozano 2015). Since medical drones can travel faster than traditional ground transport EMS vehicles, they provide the capacity to drastically reduce travel time and overall response time that is critical to the survival of SCA patients. Drones have limited range and in order to minimize response times, a network of multiple drones is required to adequately provide service to a large area. This network must be located in such a way to minimize travel delays, minimize cost, and maximize service coverage.

2.3 Spatial Optimization and Its Application in EMS

Spatial optimization is a term that refers to selecting the best spatial arrangement or allocation of services, goods, or resources (Tong and Murray 2012). Spatial optimization problems have three main components: the objective, the decisions to be made, and the constraining conditions. The objective is often constructed by using one or more mathematical function such minimization or maximization. Decision variables correspond to the choices to be made. These are the outputs of a solved optimization problem. Finally, constraints establish the conditions that are required by the problem. Constraints could relate to service levels, budget limitations, number of goods, or other requirements.

By using geographical information systems (GIS) to create relationships (proximity, connectivity, adjacency, etc.) between locations, services, and other things, many complex geographical problems can be solved (Tong and Murray 2012). There are two general strategies for solving spatial optimization problems: exact methods and heuristic methods. Exact methods exploit the properties of the problem and may exhaust all possible solutions, thus guaranteeing an optimal solution. There are many commercial and open-source software packages (Gurobi, CPLEX, GLPK, etc.) capable of solving linear and integer programming problems. Although these products work well, some optimization problems cannot be formulated as a system of linear equations. In addition, if the problem size is very large, meaning there are many constraints and decision variables, these programs may not be able to solve the problem in a reasonable amount of time. For these reasons, among others, heuristics are often used. Heuristic approaches to solving optimization problems are problem specific ad-hoc strategies that in practice find very good solutions but cannot ensure an optimal solution (Tong and Murray 2012). In general, heuristics work by exploring the solution space to find feasible solutions from which the best solution can be identified (Tong and Murray 2012).

In emergency planning, it is often necessary for EMS personnel to be able to reach a certain percentage of people or homes within a set distance or time threshold. For example, the National Fire Protection Association (NFPA) established a guideline of nine minutes between EMS notification and EMS arrival at the patient's side for 90 percent of distress calls in urban areas (Association 2010). These constraints are the basis for coverage location models. Coverage location models are a subset of spatial optimization problems where the goal is to select the best subset of sites from a set of possible locations while ensuring or maximizing the level of service provided (ReVelle and Eiselt 2005). In general, coverage location models have three main parts: the demand, the facilities that provide the service, and the demand-service constraints. In emergency planning, demand may be the total population per area unit, the number of historic emergency calls per area unit, or other related measures. The facilities represent the locations that provide some level of service to the demand. For example, these may be fire stations, hospitals, or in this case drone launch sites. Finally, the service constraints connect the facilities to the demand units by imposing restrictions on the minimum amount of demand that must be appropriately served by a configuration of facilities within a prespecified distance or time threshold. For example, the total percentage of population that can be reached by an ambulance within 5 minutes must be at least 80 percent. Coverage models have been extensively used to address emergency service planning issues and examples can be found in Murray (2013), Eaton et al. (1985), Foo et al. (2010), Pulver et al. (2016), and Erkut et al. (2008).

Pulver et al. (2016) investigated the use of *maximum coverage location problem* (MCLP) to site a network of medical drones. The MCLP, developed by Church and ReVelle (1974), is a widely-used location model to site emergency medical services. The intent of this model is to maximize the service coverage given limited resources (Church and ReVelle 1974; Church and Murray 2009, Røislien et al. 2016). Although the MCLP is widely used, it relies upon several major assumptions. The first assumption is that only one type of facility can be used. Often it may be more cost-effective to renovate existing infrastructure than to build new facilities. To address this issue, Schilling (1980) presented an extension of MCLP known as the *capital improvement model* which considers siting multiple types of facilities that have different costs.

A second major assumption of the MCLP is that it relies on binary coverage, meaning that a demand unit is either completely covered or it is not covered at all. This is not an issue when point data are used for analysis, however often, such as in this study, demand is represented as polygons where partial coverage of a polygon is possible. Many previous studies have demonstrated that significant errors in assessing service coverage and identifying optimal facility location configuration can result if partial coverage is ignored (Cromley et al. 2012; Tong 2012; Wei and Murray 2015). The difference between three coverage methods is demonstrated in Figure 2.1 where the black circles represent facilities, the dashed-grey circles represent the service areas of the facilities, the grey rectangles represent demand polygons, and the black stars represent the centroids of the demand units. First, if binary coverage, where the entire demand polygon must be serviced by at least one facility to be considered covered, is examined, only demand unit D3 is covered. Second, if binary coverage, where the centroid of the demand must be serviced by at least one facility to be considered covered, is examined, only demand units D1 and D3 are covered. In this scenario, it is clear that part of D1 is not actually covered. Finally, when partial coverage where each demand polygon may be considered partly serviced by one or many facilities, is examined, demand unit D1 is 80 percent covered, demand unit D2 is 50 percent covered, and demand unit D3 is 100 percent covered. Clearly, using partial coverage results in a more accurate estimate of the actual demand serviced. A few MCLP extensions, including the MCLP-explicit proposed by Tong and Murray (2009) and Murray et al. (2010), the MCLP-implicit developed by Alexandris and Giannikos (2010) and Murray et al. (2010), and the MCLP-complementary coverage (MCLP-CC) proposed by Tong (2012), have been developed to take into account partial coverage. Among these models, the MCLP-CC is considered to be the most promising modelling approach because of its capability of identifying facility configuration that achieves largest coverage with reasonable computational efforts (Wei 2016).

Third, the MCLP does not explicitly consider backup coverage which is important in EMS facility allocation, where a facility may be busy and unable to respond to a second event in its service area (Daskin and Stern 1981). In order to account for backup coverage, Hogan and ReVelle (1986) developed a multiobjective optimization model, which is an extension of the MCLP and known as the *backup coverage location problem* (BCLP) to maximize both primary and secondary service coverage. Several other extensions of the BCLP are also discussed in detail in Hogan and ReVelle (1986). Although these models account for backup coverage, they do not work well with continuously distributed demand, such as population. It has been shown that actual primary and secondary coverage could be overestimated or underestimated based on the binary nature of the BCLP (Kim and Murray 2008). Given this, Kim and Murray (2008) developed the BCLP-Actual Area (BCLP-AA) model, also referred to as the BCLP-Explicit by Murray et al. (2010), to deal with continuously distributed demand. However, the resulting number of constraints and variables in the BCLP-Explicit is usually very large and beyond the computational capability of existing optimization packages (Kim and Murray 2008). Such high computational requirements prohibit its application to realistic planning problems.

As described earlier, it is essential to integrate backup coverage and continuously distributed demand into the location decision making of medical drones. Given these issues associated with existing coverage models, there is a need to develop a new spatial optimization approach that explicitly takes into account backup service provision and continuously distributed demand to locate a network of medical drones.

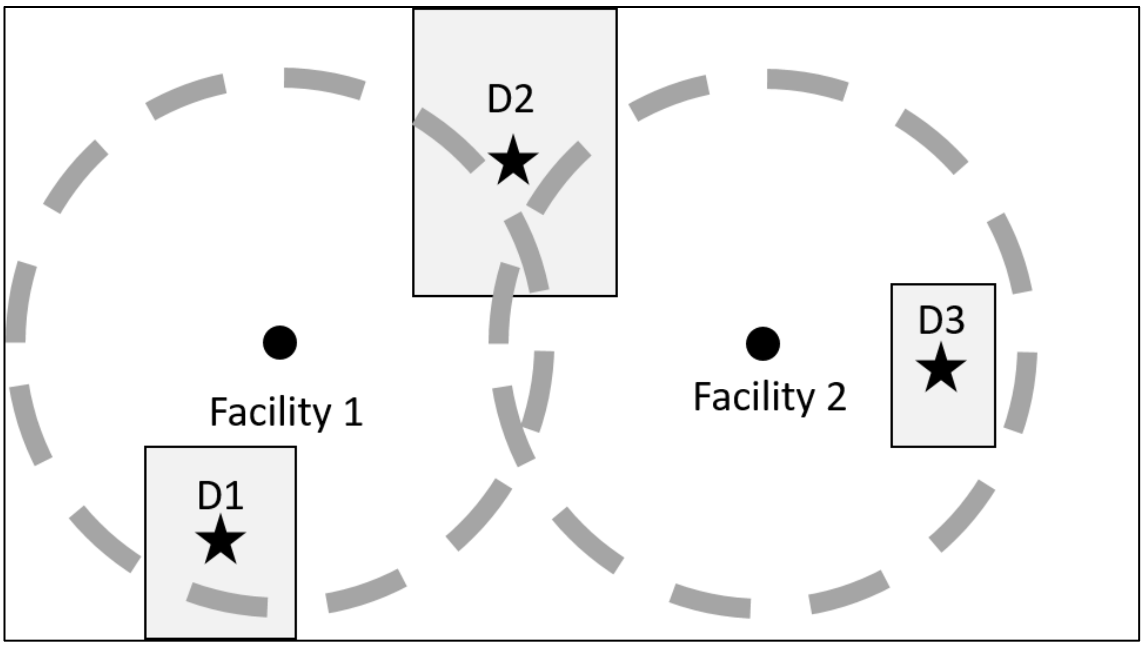

Figure 2.1 Highlighting differences between binary and complementary coverage.

CHAPTER 3

DATA

3.1 Study Area

Salt Lake County, Utah is the study area. It is the home of Salt Lake City and is located in North-Central Utah. Despite many unique geographic features such as salt flats, mountains, rivers, and canyons Salt Lake County consists of just over 1 million persons, per 2010 Census. It covers an area of just over 2000 km^2. The county was divided into 612 Census block groups which were used as demand for the location model. As shown by the dark areas in Figure 3.1, the population is most dense in the central areas of the County.

3.2 Empirical OOHCA Data

Cardiac arrest incidents from 2010-2013 were obtained from the Utah Department of Health Bureau of Emergency Services. Each incident contains demographic information about the patient, the location of the incident (at the block-group level), any associated response times and delays, the type of care (if any) given, and the patients hospital disposition. Institutional Review Board (IRB) approval was obtained from the Utah Department of Health and an exemption was granted by the University of Utah IRB.

As shown in Table 3.1, there were 2044 total incidents that were used in this study. The table is broken into several demographics (age, sex, race, and ethnicity). Not every record had all of the reported attributes. Therefore, in each category the “total” refers to the total number of patients that had information corresponding to that category. The majority of the patients were age forty-five or older, corresponding with most literature. Over 63 percent of the patients were male, which is definitely within the range supported by similar studies. Nearly 85 percent of the victims were white. However, once the data is normalized by 2010 Census demographic data, a larger percentage of black persons suffer cardiac arrest than white persons. This matches results found in previous studies. Similarly, non-Hispanics have higher normalized incidence rates than Hispanics.

Information about the incidents was also summarized and is presented in Table 3.2. 56 percent of the incidents were not witnessed, which does not bode well for survival rates. The majority of patients with a recorded initial heart rhythm had an Asystole (“flat-line”) rhythm. Only 22 percent of patients had a ventricular fibrillation (VF) or ventricular tachycardia (VT) rhythm, two of the most shockable rhythms.

Perhaps the most pertinent information for this study is the estimated time of arrest prior to emergency medical service (EMS) arrival. Over 41 percent of victims were estimated to have experienced the SCA over twenty minutes before EMS arrived on scene. It’s highly likely that these patients were dead on arrival. Only 12.6 percent of victims had EMS on scene within four minutes. It’s important to note that this includes the time it takes for the victim or a bystander to recognize the symptoms of sudden cardiac arrest (SCA) and call EMS as well as dispatch and travel delays. Travel times are shown in histogram in Figure 3.2. It is clear that the majority of incidents required six or fewer minutes of EMS travel.

Automated external defibrillator (AED) defibrillation was used in 28.5 percent of cases whereas chest compressions were applied in 68.7 percent of cases. This may be tied closely to the initial rhythm; only certain rhythms are shockable. In addition, AED use prior to EMS arrival was only performed in 8 percent of cases. These two statistics suggest that there is significant room for improvement in AED access and use.

Nearly 90 percent of incidents were responded to within seven minutes of notification. However, the majority of those took four to seven minutes, which while still good, may not be fast enough for SCA.

Forty-one percent of calls resulted in a death at the scene. Fifty-six percent of patients were successfully treated at the scene and possibly transported to a hospital. Of the incidents that were linked to hospital records, 64 percent of patients died at the hospital.

The crude incident rates are mapped in Figure 3.3 Dark areas represent areas with high incidence rates; light areas represent areas with low incident rates. It is worth noting that incidents were assumed to be uniformly distributed inside each block group. The larger block groups shown in the Eastern and Western sections of Figure 3.3 are mountainous areas with lower populations.

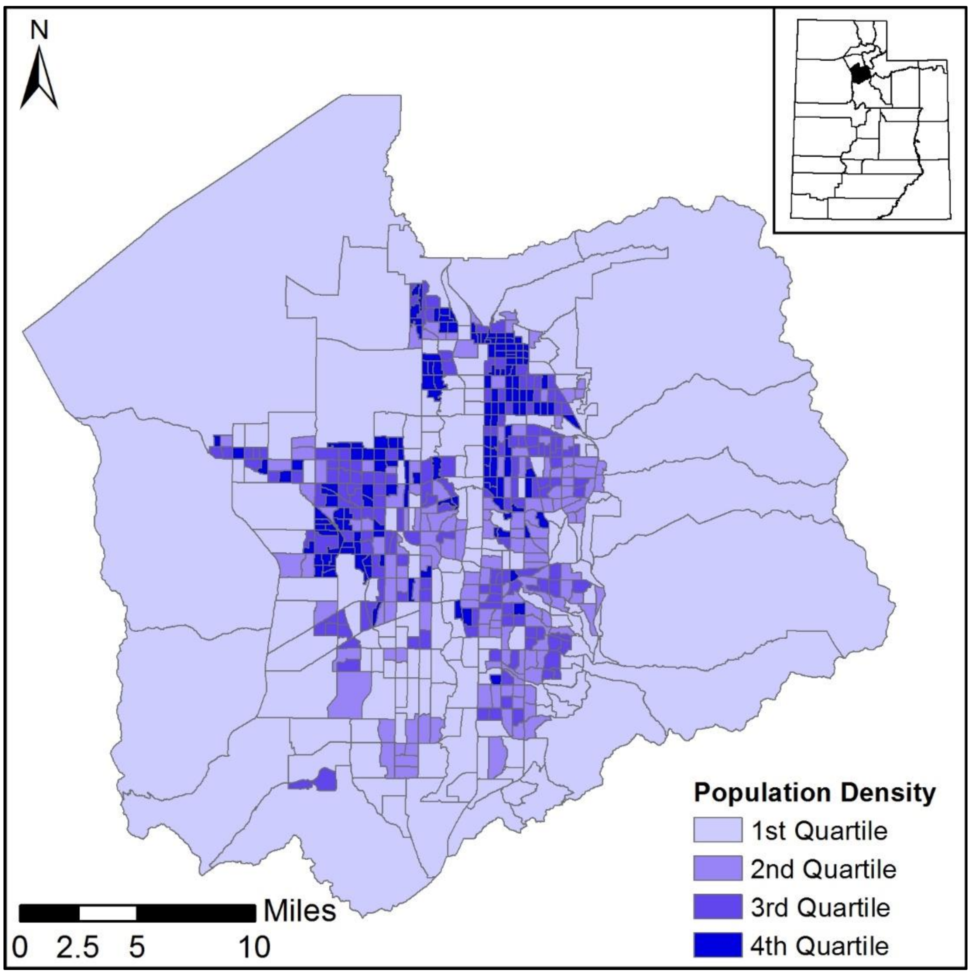

Figure 3.1 Population density of Salt Lake County.

Table 3.1 Demographics of patients used in study.

		N	%	% 2010
Total		2044	100.00	
Age	Total	1984		0.19
	<18	87	4.39	0.03
	18-34	231	11.64	0.08
	35-44	170	8.57	0.13
	45-54	269	13.56	0.22
	55-64	411	20.72	0.43
	65-74	351	17.69	0.71
	75-84	272	13.71	0.97
	>=85	193	9.73	1.65
	Unknown	60		
Sex	Total	1966		0.19
	Male	1242	63.17	0.24
	Female	724	36.83	0.14
	Unknown	78		
Race	Total	859		0.08
	White	726	84.51	0.03
	Black	26	3.03	0.11
	Asian	18	2.10	0.04
	American Indian, Alaska Native	5	0.58	0.03
	Native Hawaiian, Other Pacific Islanders	24	2.79	0.12
	Other	60	6.98	0.06
	Unknown	1185		
Ethnicity	Total	533		0.05
	Hispanic	47	8.82	0.03
	Not Hispanic	486	91.18	0.06
	Unknown	1511		

Table 3.2 Incident characteristics.

		N	%
Witnessed	Total	1908	
	Lay Person	639	33.49
	Healthcare Provider	196	10.27
	Not Witnessed	1073	56.24
	Unknown	136	
Initial Rhythm	Total	1830	
	Asystole	1061	57.98
	Bradycardia	28	1.53
	Normal Sinus Rhythm	17	0.93
	PEA	214	11.69
	Unknown AED Nonshockable	32	1.75
	Unknown AED Shockable	20	1.09
	VF	376	20.55
	VT	29	1.58
	Other	53	2.90
	Unknown/NA	214	
Estimated Time of Arrest Prior to	Total	1666	
	0-2	123	7.38
	2-4	87	5.22
	4-6	194	11.64
	6-8	93	5.58
	8-10	140	8.40
	10-15	219	13.15
	15-20	126	7.56
	>20	684	41.06
	Unknown	378	
Resuscitation Attempted	Total	1722	
	AED Defibrillation	492	28.57
	Chest Compressions	1183	68.70
	Ventilation	928	53.89
	Not Attempted	440	25.55
	Unknown	354	
Prior Aid	Total	233	
	AED	19	8.15
	CPR	167	71.67
Prior Aid Performed by	Total	144	
	EMS/Healthcare Provider	56	38.89
	Law Enforcement	29	20.14

Table 3.2 Continued

		N	%
	Lay Person	58	40.2
	Patient	1	0.69
	Unknown	1900	
Notified to On Scene	Total	2032	
	<2	30	1.48
	2-3	318	15.6
	4-5	877	43.1
	6-7	588	28.9
	8-9	177	8.71
	10-14	64	3.15
	15-19	5	0.25
	>=20	3	0.15
	Other	12	
Incident Disposition	Total	2044	
	Dead at Scene	856	41.8
	Cancelled	14	0.68
	No Treatment Required	15	0.73
	Treated	1158	56.6
	Refused Care	1	0.05
Hospital Disposition	Total	270	
	Deceased	174	64.4
	Discharged to Home	49	18.1
	Discharged/Transferred to	47	17.4

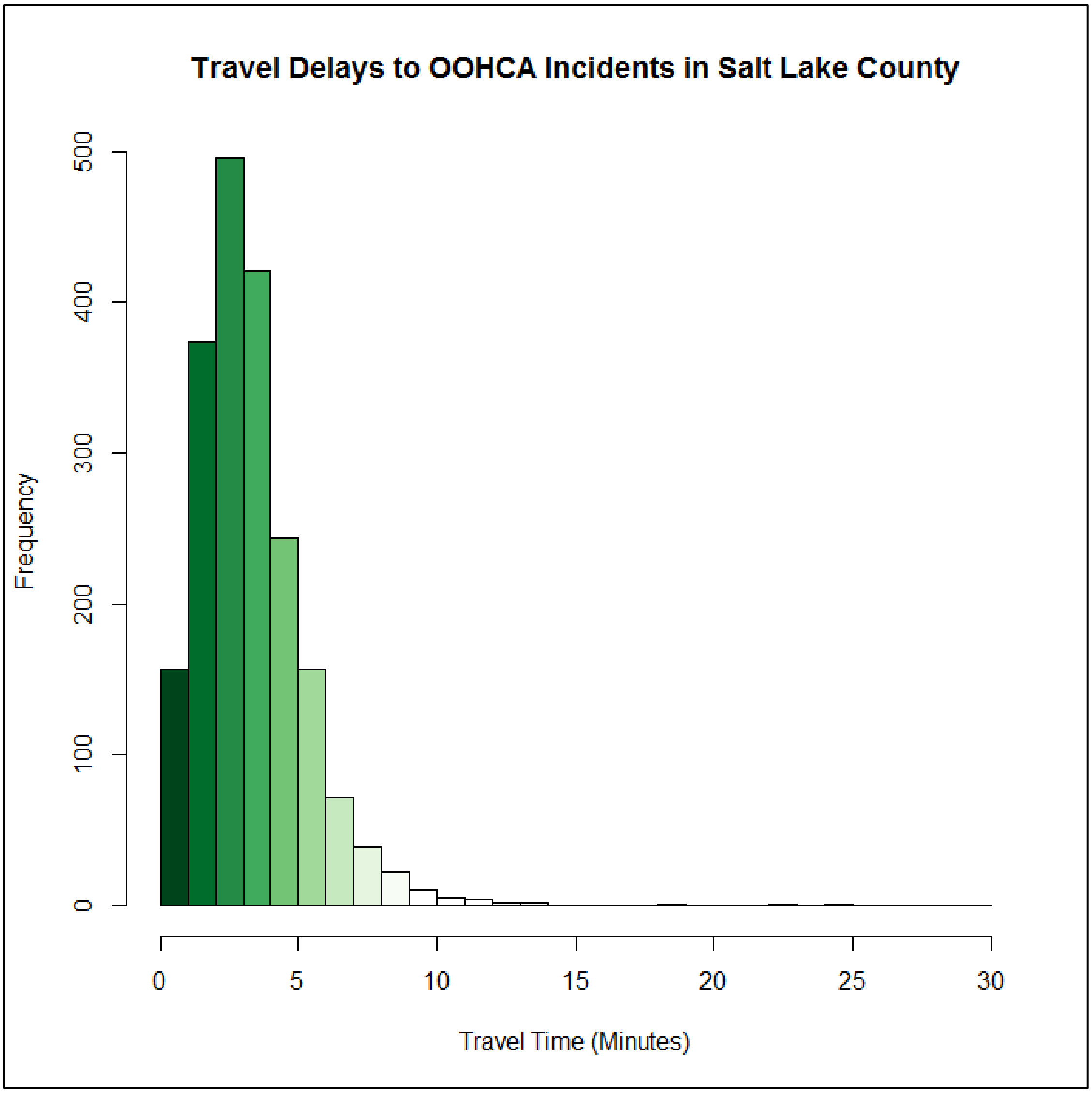

Figure 3.2 Travel delays to OOHCA incidents in Salt Lake County.

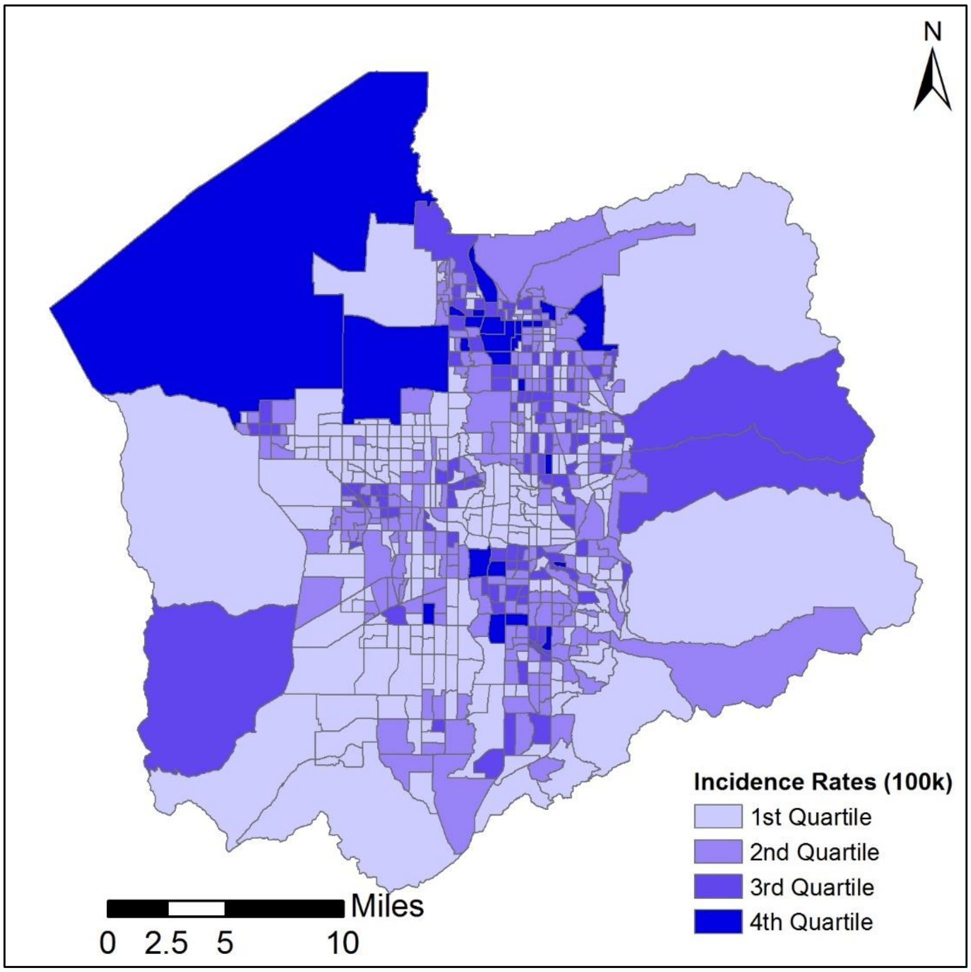

Figure 3.3 Out-of-hospital cardiac arrest incidence rates in Salt Lake County.

CHAPTER 4

METHODOLOGY

4.1 Determining Importance of Factors Related to OOHCA Incident Disposition

As this study is focused on using medical drones to reduce medical equipment travel time, an important step is to determine the importance of response time and automated external defibrillator (AED) defibrillation relating to out-of-hospital cardiac arrest (OOHCA) survival in Salt Lake County. As previously mentioned, six major factors have been determined to significantly effect a patient's survival outcomes: (1) initial heart rhythm (2) rescue team response time, (3) location of arrest, (4) witnessed status, (5) bystander cardiopulmonary resuscitation (CPR), and (6) age. Random forests are a common machine learning classification technique that can model nonlinear relationships well. This study uses the random forest model proposed by Breiman (2001) to examine the relative importance of age, sex, race, response travel time, first rhythm, defibrillation, ventilation, and chest compressions relating to OOHCA on-scene survival rates.

Random forests are a combination of tree predictors such that each tree is derived from a random vector sampled independently and with the same distribution for all trees in the forest (Breiman 2001). A binary classification tree is an input-output model represented by a tree structure consisting of several nodes. Any node in the tree represents a subset of the total space and is labelled with a binary split so that it has two child nodes.

An example decision tree is shown in Figure 4.1 where three variables are used to classify a patient as dead or alive. The first check is if the patient is male or not. If the patient is a male, then a second check if performed to check the age of the patient. If the patient is older than sixty-five, then a final decision is performed using travel time. All leaf nodes represent one of two states: survived or died. By traversing a tree until a leaf node is reached, the outcome of a specific patient can be determined. A tree is created from a dataset using a recursive process which identifies at each node the splitting criteria that maximizes the decrease of some impurity measure such as the Gini impurity (Louppe et al., 2013). The Gini impurity is a measure of how often a randomly selected item from the set would be incorrectly labelled if it was randomly labelled according to the distribution of the labels in the subset. If a node has a proportion of p_j for each class j, then the Gini impurity is defined as:

$$i(p) = 1 - \sum_j {p_j}^2 \tag{4.1}$$

Basically, the average Gini impurity is calculated for each class that could be used to split the dataset, the class that results in the lowest impurity is then used as the splitting variable. The construction of the tree stops when nodes become pure, meaning that there is only one class contained in that node (Louppe et al., 2013). Since single trees tend to suffer from high variance, which results in poor prediction accuracy, several ensemble methods such as random forests have been explored.

In random forests, each tree is fully grown using a random permutation of the original data; no pruning is performed. This results in a set of decision trees, with unique splitting criteria. From the complete forest, the status of the response variable is predicted as a majority vote of the individual predictions by all trees (Strobl et al. 2007). Classification trees and random forests can be used to assess the importance of covariates. By calculating the *Gini importance* or *Mean Decrease Accuracy* for each prediction variable, the relative importance of prediction variables can be observed. The *Gini importance* is based on the average Gini impurity used for calculating splits during training of the trees (Louppe et al., 2013). By ranking the magnitude of the decrease of the average Gini impurity for each class, the importance of each class is ranked accordingly. The *Mean Decrease Accuracy* is the number of misclassifications produced when the specified feature is emitted from the random forest (permutated). The randomForest package in R, a free open source statistical programming language, was used to create a random forest using 1000 binary classification trees.

4.2 Determining Potential Launch Sites

Since the primary objective of this study is to optimize the placement of medical drone launch sites, an initial set of potential launch points must be determined. Two types of launch sites are considered in this study. First, existing emergency medical service (EMS) facilities in Salt Lake County are considered as significant infrastructure is already in place. These facilities were geocoded using addresses provided by the Utah Department of Health. Second, new launch sites are proposed to add additional potential coverage. Since the proposed medical drones are small and ideally require little infrastructure to be launched, it is reasonable to assume that they can be deployed from nearly anywhere in the county. In order to reduce the infinite set of launch sites to a reasonable set of discrete points for analysis, the finite dominating set (FDS) methodology proposed by Murray and Tong (2007) was employed. The FDS along with the set of existing EMS stations were used as potential launching platforms. There were a total of 1608 possible launch sites, each with the capacity to launch up to two drones.

4.3 Distance Calculations and Service Areas

Emergency service providers are generally required to meet certain response time requirements. For example, the Salt Lake City Fire Department aims to maintain an average response time of five minutes or less for all life-threatening emergencies (City Council 2014). Pulver et al. (2016) showed that over 80 percent of the population in Salt Lake County can be responded to within 5 minutes by the current EMS infrastructure. However, this study employs a minimum coverage of 90 percent for a one-minute time standard, S_1, due to its significant correlation to high survival rates. Considering the top speed for a drone is 60 mph, a service range of 1609 km, corresponding to a travel time of one minute, was used for each potential facility to determine the service area. Each facility was therefore buffered using ArcGIS to 1609 km to create a circular service area. For the purpose of this research, the time interval associated with EMS response that represents the actual travel time to deliver an AED to the patient was focused on.

4.4 Modelling – The BCLP-CC

Due to the limitations of the *maximum coverage location problem (*MCLP) and the need to explicitly account for backup coverage, a new multiobjective model, the *backup coverage location problem with complementary coverage* (BCLP-CC), is proposed to identify the optimal locations for a network of medical drone launch sites. The BCLP-CC is an extension of both the BCLP and MCLP with some constraints similar to the MCLP-CC. This model accounts for partial coverage of continuously distributed demand as well as backup coverage. The BCLP-CC uses the following notation:

$j =$ index of potential drone launch sites where $j = 1,2, \dots m$

$i =$ index of demand units where $i = 1,2, \dots n$

$d_i =$ amount of demand in unit i

$p =$ number of drone launch sites to locate

$h =$ maximum backup coverage level

$b_{ij} =$ the amount of service provided to demand i by the drone launched at j

$t =$ the maximum response time used to determine service areas

$N_i =$ the set of drone launch sites that provide some service to demand i within t

$X_j =$ the number of drones launched from site j

$Z_i =$ the amount of total overall coverage received by demand unit i

$Y_i =$ the amount of backup coverage received by demand unit i

$W_i =$ the amount of primary coverage received by demand unit i

The potential drone launch sites and demand units are denoted by indices i and j, respectively. The amount of demand in each unit i is denoted as d_i. The maximum level of backup coverage to allow is defined by h. For example, setting h = 2 means that only primary and secondary coverage are considered and additional coverage provided by three or more drones is not taken into account. The h is prespecified and could be determined by the characteristics of demand volume. The amount of partial service provided to demand unit i by the drone launched at site j is defined by b_{ij}. A response time threshold for the model is defined as *t*. This could be one hour, ten minutes, or in this specific study, one minute. The set of drone launch sites that are able to provide partial or full service to demand unit i within the specified time threshold t is denoted as N_i. X_j are decision variables, indicating the number of drones that will be launched from site j. The total overall coverage received by demand unit i is denoted by Z_i. The total overall coverage can be broken into two components: W_i, the primary coverage, and Y_i, the backup coverage.

Given this notation, the BCLP-CC model is outlined as follows:

$$\text{Max } \sum_{\mathrm{i}} W_i \tag{4.2}$$

$$\text{Max } \sum_{\mathrm{i}} Y_i \tag{4.3}$$

Subject To:

$$\sum_{j \in N_i} b_{ij} X_j \geq Z_i \text{ , } \forall \mathrm{i} \tag{4.4}$$

$$Y_i \leq Z_i - d_i, \forall i \tag{4.5}$$

$$W_i \leq Z_i, \forall i \tag{4.6}$$

$$W_i \leq d_i, \forall i \tag{4.7}$$

$$Z_i \leq h d_i, \forall i \tag{4.8}$$

$$\sum_j X_j \leq p \tag{4.9}$$

$$X_j \geq 0 \text{ and integer for each } j = 1,2, \dots, m \tag{4.10}$$

$$W_i, Z_i \geq 0 \text{ for each } i = 1,2, \dots, n \tag{4.11}$$

The first objective (4.2) is to maximize the total amount of primary coverage for demand. The secondary objective (4.3) is to maximize the total amount of backup coverage for demand. Constraints (4.4) track all the partial coverage provided by single or multiple drone launch sites for each demand unit. Constraints (4.5) determine the approximate backup coverage provided to each demand unit. Constraints (4.6) and (4.7) ensure the primary coverage to be no more than total overlapping coverage received and actual demand at unit i. Constraints (4.8) stipulate the maximum backup coverage level that is considered by ensuring the amount of overall coverage for each demand unit will not exceed hd_i. Constraint (4.9) specifies that p drones will be launched. Constraints (4.10) impose integer restrictions on X_j. Constraints (4.11) ensure nonnegativity requirements for W_i and Z_i.

Compared to the MCLP, the BCLP-CC maximizes both primary coverage and backup coverage, enabling it to identify a spatial configuration of drone launch sites that can significantly improve backup coverage with little to no loss of primary coverage. To eliminate the need for discrete demand representation, the BCLP-CC relies on the complementary coverage approach developed by Tong (2012) to account for areas that are partially covered by one or more facilities.

The BCLP-CC is a multiobjective model, requiring identification of trade-off solutions using multiobjective solution techniques. One popular approach is the weighting method, where the two objectives are combined using a weight *w* (Houck and Cohon 1978). This is accomplished as follows:

$$\text{Max } (1 - w_b) \sum_i W_i + w_b \sum_i Y_i \tag{4.12}$$

Objectives (4.2) and (4.3) can be replaced by objective (4.12), and the model can be solved as a single objective optimization model. By varying the backup coverage weight, w_b, from 0 to 1, different problem scenarios arise and various trade-off solutions can be identified.

Clearly, the BCLP-CC is more mathematically complex than the MCLP and the BCLP due to the integration of backup coverage and continuously distributed demand. Consider an application with n potential launch sites and m demand units. The BCLP-CC has $3n + m$ decision variables and $5n + 1$ constraints. The MCLP has $m + n$ decision variables and $n + 1$ constraints. The BCLP has $2n + m$ decision variables and $2n + 1$ constraints. However, when compared to the BCLP-AA which has $nm^2 + (n + 1)m$ decision variables and $n(2 + m + m^2) + 1$ constraints, the BCLP-CC is considerably less complex (Kim and Murray 2008). In addition to the reduced complexity, the BCLP-CC includes an additional degree of freedom, h, that can be changed to vary the level of backup coverage to optimize (e.g., 2 = secondary, 3 = tertiary).

The BCLP-CC assumes that the costs to establish all the potential drone launch sites are the same. However, as detailed previously, the potential drone launch sites consist of ones that are upgraded from existing EMS stations and new facilities. Given it is more expensive to establish new facilities than to upgrade existing facilities, the BCLP-CC can be extended to the *backup coverage location problem with complementary coverage and capital improvement* (BCLP-CCCI) to takes into account locating new facilities as well as upgrading existing facilities. Consider the following additional notation:

$N_1 =$ the set of new facilities, a subset of N

$N_2 =$ the set of existing facilities, a subset of N and the complement of N_1

$k =$ number of existing facilities to locate

Constraints (4.4) must be modified to use this new notation as follows:

$$\sum_{j \in N_1} b_{ij} X_j + \sum_{j \in N_2} b_{ij} X_j \geq Z_i \text{ , } \forall i \qquad (4.13)$$

Constraints (4.8) must also be modified to use the more specific sets of facilities:

$$\sum_{j \in N_1 \& N_2} X_j \leq p \qquad (4.14)$$

Finally, constraint (4.15) must be added to limit the number of existing facilities to locate:

$$\sum_{j \in N_2} X_j \leq k \qquad (4.15)$$

By iterating over the permutations of p and k, the ideal number of existing facilities to be modified and new facilities to be built can be found to minimize total implementation cost.

4.5 Model Implementation

The coverage provided by each potential facility was computed by overlaying the service area with the demand polygons and interpolating the demand. This was performed in Python, a free open source programming language, using the Arcpy library associated with ArcGIS. The BCLP-CC model was then formulated in Python using the derived coverages and solved using Gurobi, a commercial linear programming solver. The BCLP-CC model and analysis was performed on an Intel Core i7 4770 CPU @ 3.40 GHZ with 16.0 GB of random access memory (RAM). The BCLP-CCCI model and analysis was performed on a dual processor Intel Xeon CPU E5-2680 @ 2.80GHz with 32 GB of RAM. A time limit of 1000 seconds was set for each iteration.

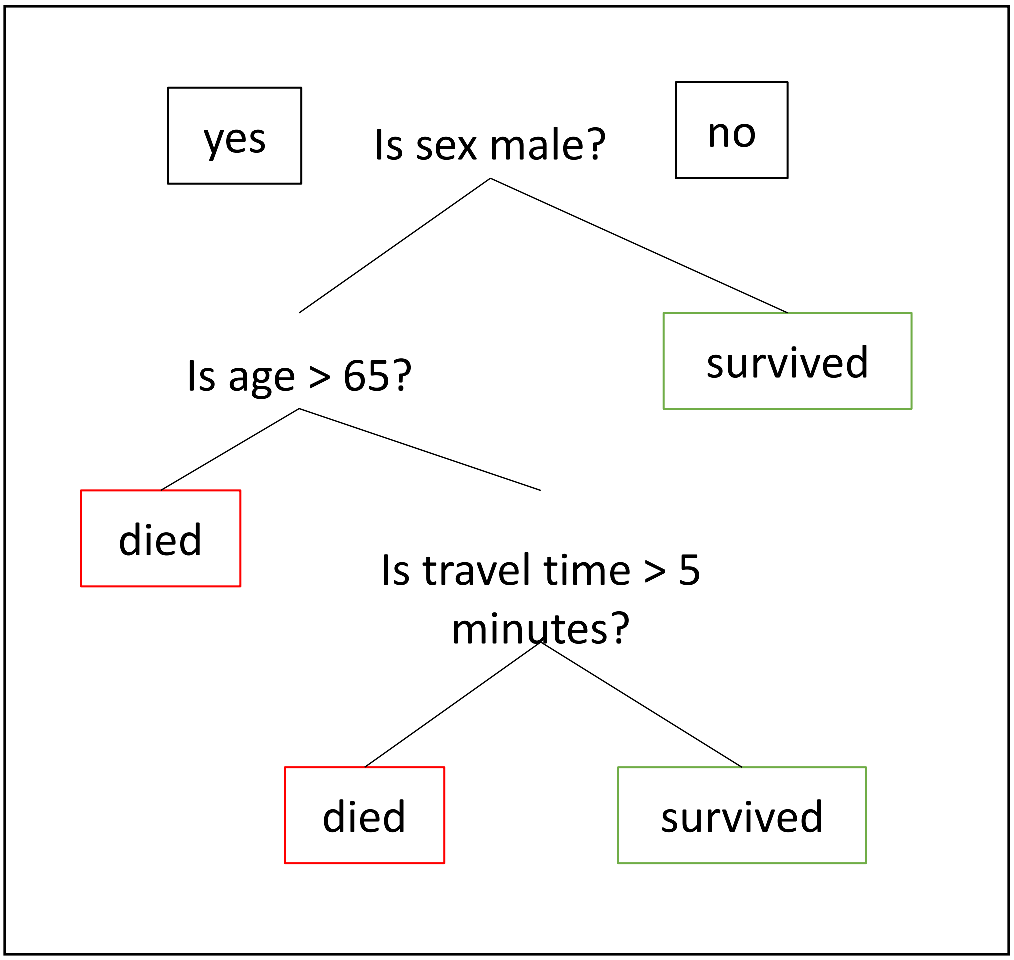

Figure 4.1 Example decision tree.

CHAPTER 5

RESULTS

5.1 Important Factors Contributing to SCA Survival in Salt Lake County

The primary goal of this study is to reduce emergency medical service (EMS) response times with the objective of improving out-of-hospital cardiac arrest (OOHCA) survival rates. Therefore, it is necessary to show that lower EMS travel times are statistically tied to higher survival rates. The 2044 medical incidents were filtered to find records that contained valid data for all of the following factors:

1) On-scene disposition (alive, dead)
2) Age of the patient (in years)
3) Sex (male, female)
4) Race (white, black, Asian, American Indian, Native Hawaiian/Pacific Islander)
5) Witnessed by layperson or healthcare provider (yes, no)
6) Notification to on-scene delay (minutes)
7) EMS travel time (minutes)
8) Chest compressions applied by EMS personnel (yes, no)
9) Ventilation applied by EMS personnel (yes, no)
10) Defibrillation applied by EMS personnel (yes, no)
11) First rhythm detected (asystole, bradycardia, PEA, VF, VT, normal sinus rhythm,

unknown shockable, unknown unshockable)

12) Estimated time of cardiac arrest prior to EMS arrival (minutes)

Records where the estimated time of cardiac arrest was greater than or equal to twenty minutes were filtered out as well in an attempt to eliminate patients that were likely dead on arrival of EMS. The resulting set of 282 records was used to train a random forest, using 1000 trees and binary splitting, to classify the patient's outcome. The out-of-bag (OOB) error was 17.02 percent meaning that 83 percent of the outcomes were successfully predicted after permuting the data. The mean decrease in accuracy and the mean decrease in Gini importance are show in Figures 5.1 and 5.2. As you can see in both figures, age, travel time, and the first rhythm detected are the most imperative factors as determined by both measures of importance. As mentioned previously, and now shown with empirical data, travel time remains one of the most important factors for cardiac arrest survival. By reducing travel times, which is the main goal of this study, it is expected that more lives will be saved.

5.2 BCLP-CC Results

Now that a low EMS travel time has been shown to be crucial to sudden cardiac arrest (SCA) survival, steps can be taken to implement a network of medical drones to reduce EMS response time with the intention of improving SCA survival rates. The first step of determining the optimal configuration of drone launch sites was to evaluate the *backup coverage location problem with complementary coverage (*BCLP-CC) and show that it accomplishes its goal of significantly increasing backup coverage while not hindering primary coverage. In addition, several model parameters must be selected based on the study area, empirical data, and desired results.

Ideally, a network of medical drones would be able to serve 90 percent of the historical demand for EMS due to cardiac arrest. The empirical OOHCA incident rates, at the block group level, were used as demand polygons for the BCLP-CC model. In addition, one set of potential facilities, consisting of both existing and new sites, was used. To identify the optimal facility configuration, the BCLP-CC was solved iteratively, varying the number of drone launch sites from p = 1 to p = 75. Since this study is primarily concerned with primary and secondary coverage, h was set to 2.

Figure 5.3 shows how as the number of drones and launch sites increases, the total amount of primary and secondary coverage increases for three different scenarios or weights for backup coverage. When backup coverage is not accounted for, w_b = 0.0, a minimum of fifty-six drones is required meet the 90 percent coverage requirement. This results in only 19 percent of the demand being covered twice, which may not be sufficient for city planners. The resulting spatial configuration is shown in Figure 5.4. Launch sites represented by triangles deploy two drones; launch sites represented by circles deploy only one drone. Rather than having two launch sites nearly on top of each other, it makes more sense, from a practical perspective, to have one launch sites deploy multiple drones.

Increasing the weight w_b to 0.2 required the use of seventy-one drones and sixty-eight launch sites to cross the 90 percent coverage threshold at 90.3 percent, where three launch sites have the potential to deploy two drones (Figure 5.5). This situation resulted in 58.9 percent backup coverage, an improvement of 40 percent when compared to the model which has a backup coverage weight of 0.0.

In addition, when backup coverage is solely optimized ($w_b = 1.0$), the primary coverage closely matches the backup coverage, as shown in Figure 5.3. This is expected as the model is seeking to optimize the amount of overlapping areas; ideally every area would be overlapping. This model was unable to reach the desired threshold of 90 percent primary coverage (with a maximum of seventy-five drones), however it was able to provide 84.3 percent primary coverage and 74.9 percent backup coverage. The spatial configuration is shown in Figure 5.6. Clearly the launch sites are much closer together, resulting in high backup coverage.

With three varying results, it's clear that the weight must be chosen in a meaningful manor. This can be done by plotting the primary and backup coverage against the weight. For example, Figure 5.7 plots such trade-off curves when fifty drones are located. Clearly, as the backup weight, w_b, increases, the amount of backup coverage increases approximately logarithmically and the amount of primary coverage decreases approximately linearly. As w_b increases from 0.0 to 0.2, the backup coverage increases relatively quickly. Beyond 0.2, the backup coverage begins to increase at a slower rate. Therefore, 0.2 was chosen as the backup weight as it provides significant increases in backup coverage with minimal loss to primary coverage.

Comparing the spatial distribution of drones in Figure 5.5 with the spatial distribution of incidence rates in Figures 3.3 shows that only areas that have medium to high incidence rates are covered. For example, there is area in the center of the map that has low incidence rates, represented by lightly coloured polygons in Figure 3.3; in all three spatial configurations this area is not covered. This is expected and intuitively validates the model. Drone launch sites that are in areas of very high demand were not only selected in the model, but were selected to launch multiple drones.

5.3 BCLP-CCCI Results

Although the previous results show the effectiveness of the BCLP-CC, the BCLP-CC does not inherently optimize for lowest cost implementation. By breaking the set of possible facilities into two distinct groups of new facilities and existing facilities and by applying costs to each type of facility as well as to each drone, the total cost of different drone network configurations can be compared and contrasted.

Assuming it costs approximately $50,000 to establish a new drone launch site, $10,000 to customize an existing site, and $20,000 to purchase an AED-enabled drone, the optimal configurations for two scenarios were determined. The first scenario uses the 2010 Census population per block group as demand for the modified *backup coverage location problem with complementary coverage and capital improvement* (BCLP-CCCI) using a backup weight (w_b) of 0.2 (Figure 5.8). This resulted in a total cost of $5,610,00 to cover at least 90 percent of the population by using 119 drones, 48 existing facilities, and 55 new facilities. The second scenario uses the crude incidents rates as demand for the BCLP-CCCI using a backup weigh of 0.2 (Figure 5.9). This resulted in a total cost of $3,980,000 to cover at least 90 percent of the demand by using drones, forty-four existing facilities, and twenty-six new facilities. This resulted in 65 percent of the demand being covered a second time. Compared to the previous BCLP-CC results which used seventy-one drones, three existing facilities, and sixty-seven new launch sites and resulted in a total cost of $4,800,000, the result of the BCLP-CCCI reduced implementation costs by $800,000 (17 percent).

Clearly, it costs significantly more to adequately cover at least 90 percent of the population than it does to cover 90 percent of historical incidents. This was expected based on the spatial patterns of the demand shown in Figure 3.1 and 3.2. The population in Salt Lake County is much more evenly distributed than the crude incidents rates, where many block groups have no reported incidents.

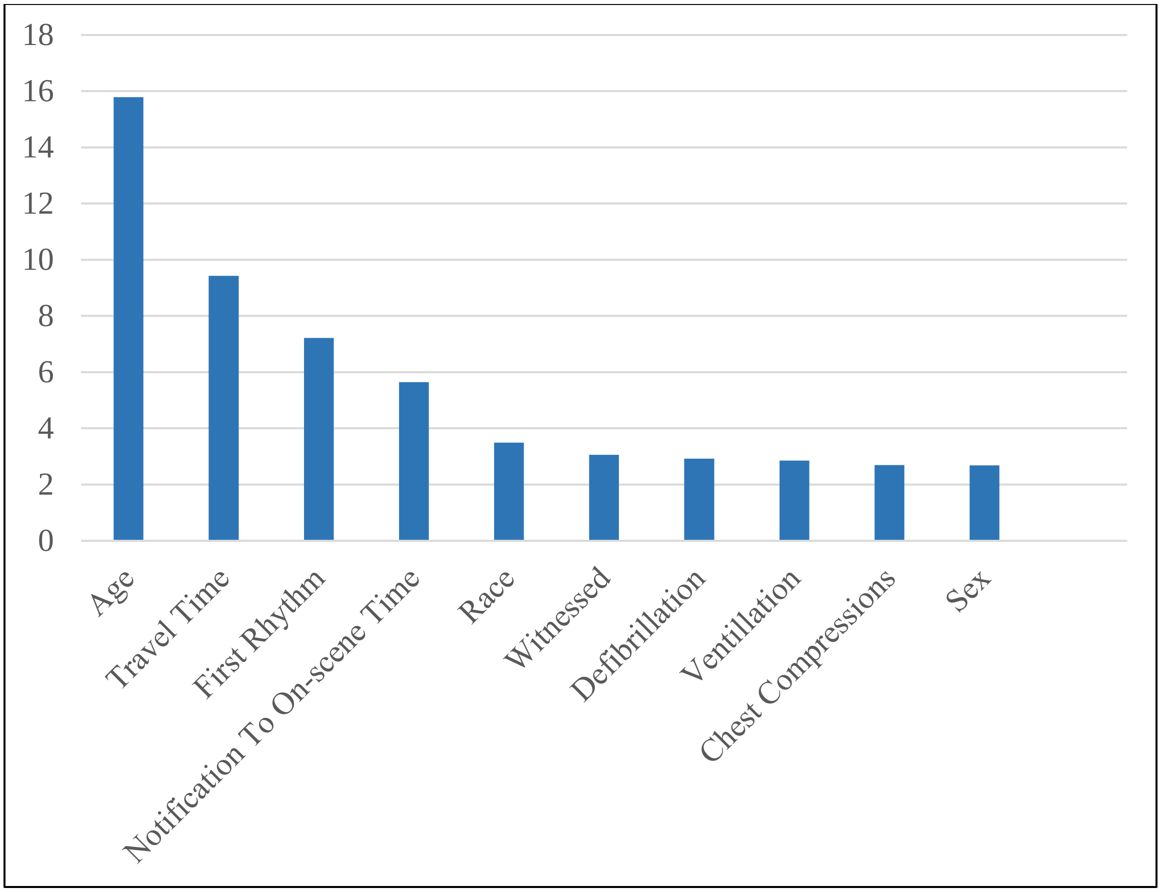

Figure 5.1 Variable importance plot using mean decrease in Gini.

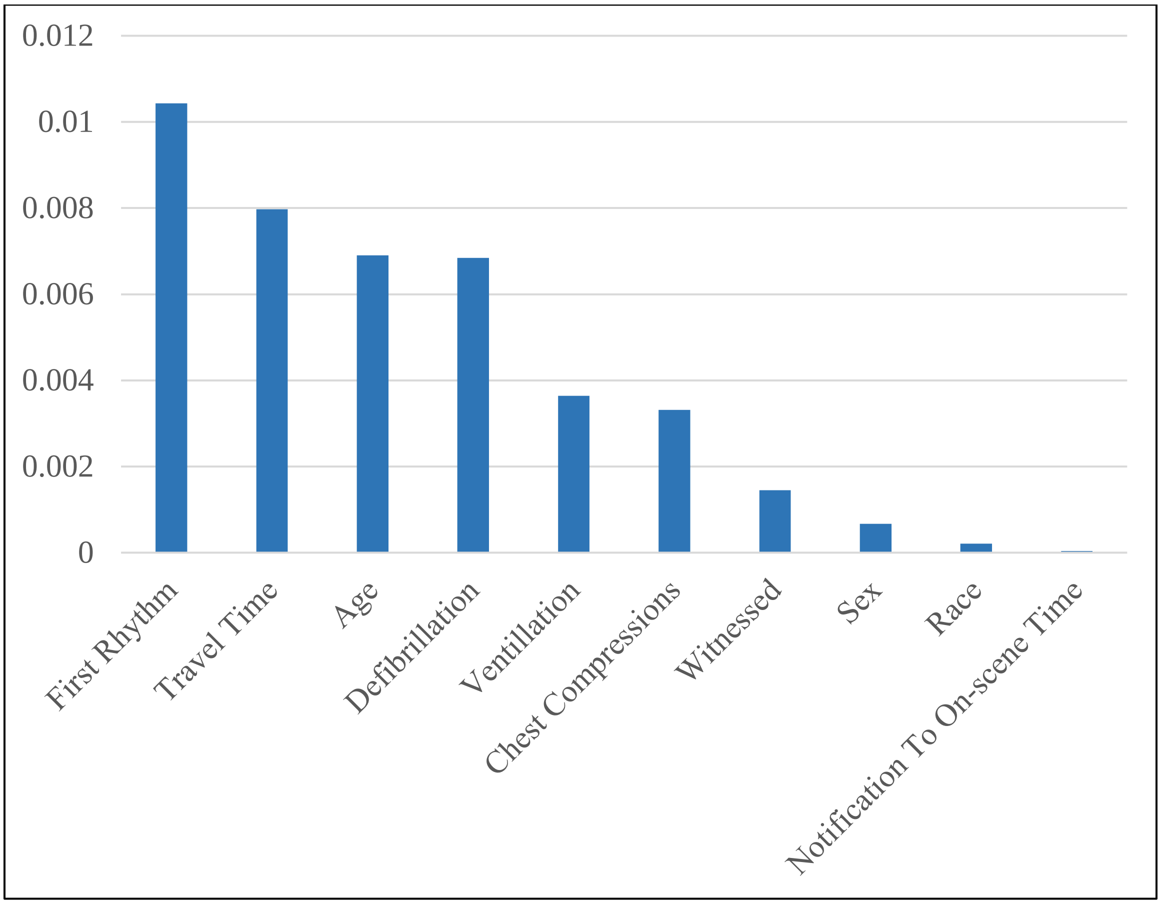

Figure 5.2 Variable importance plot using mean decrease in accuracy.

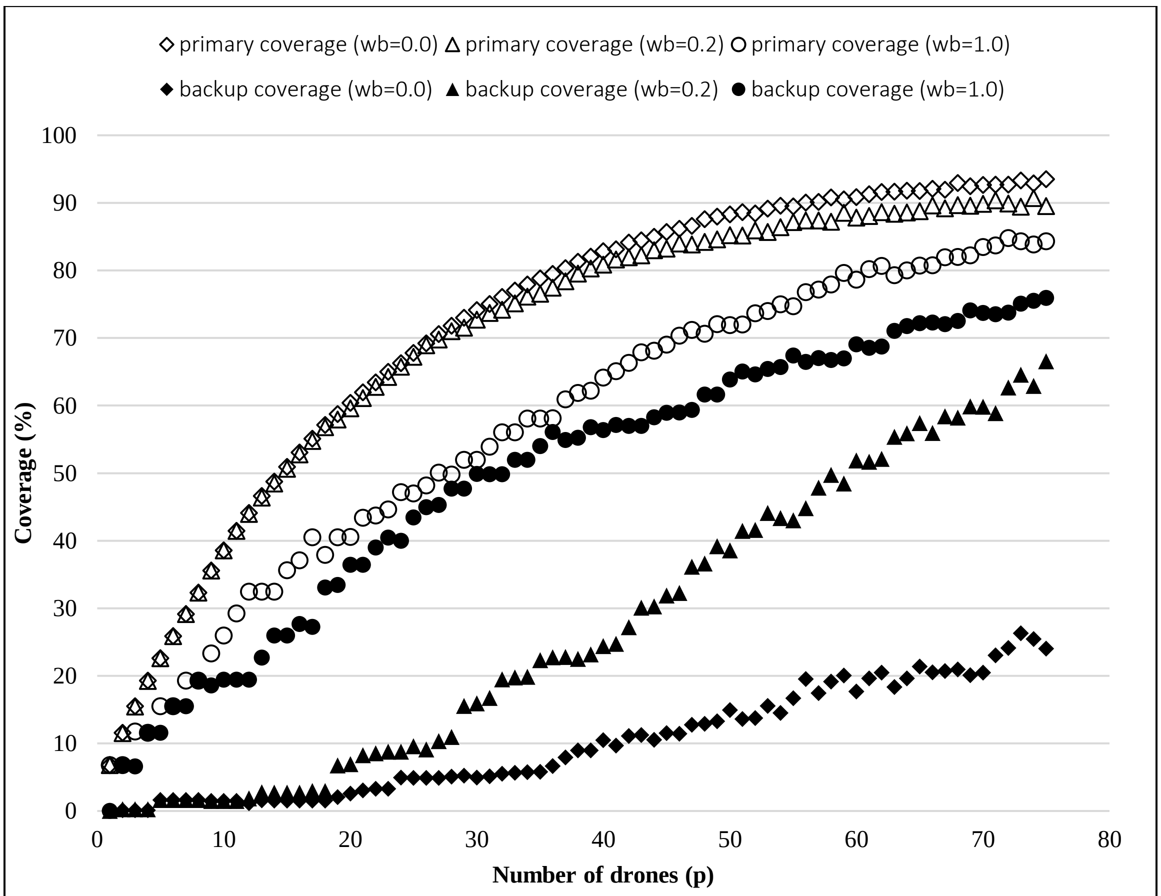

Figure 5.3. Primary and secondary coverage achieved when w_b = 0.0, 0.2, and 1.0.

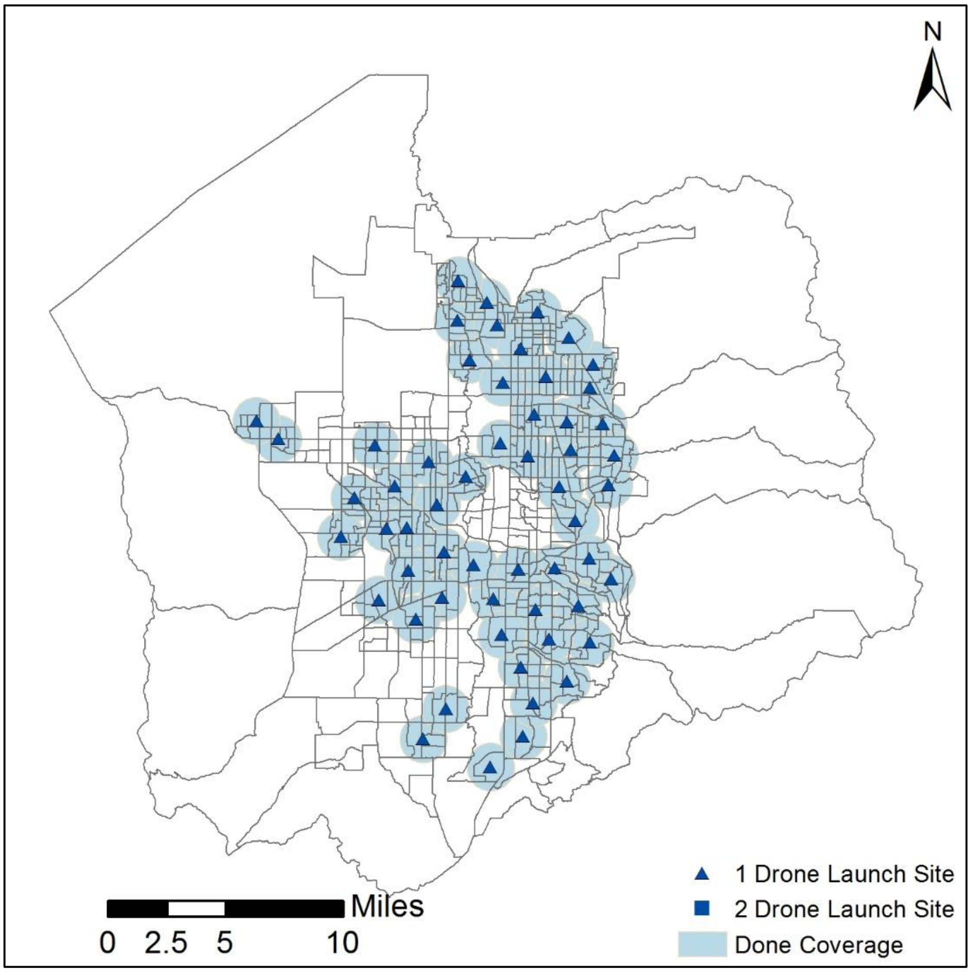

Figure 5.4 Identified spatial configuration of drones using BCLP-CC when $w_b = 0.0$.

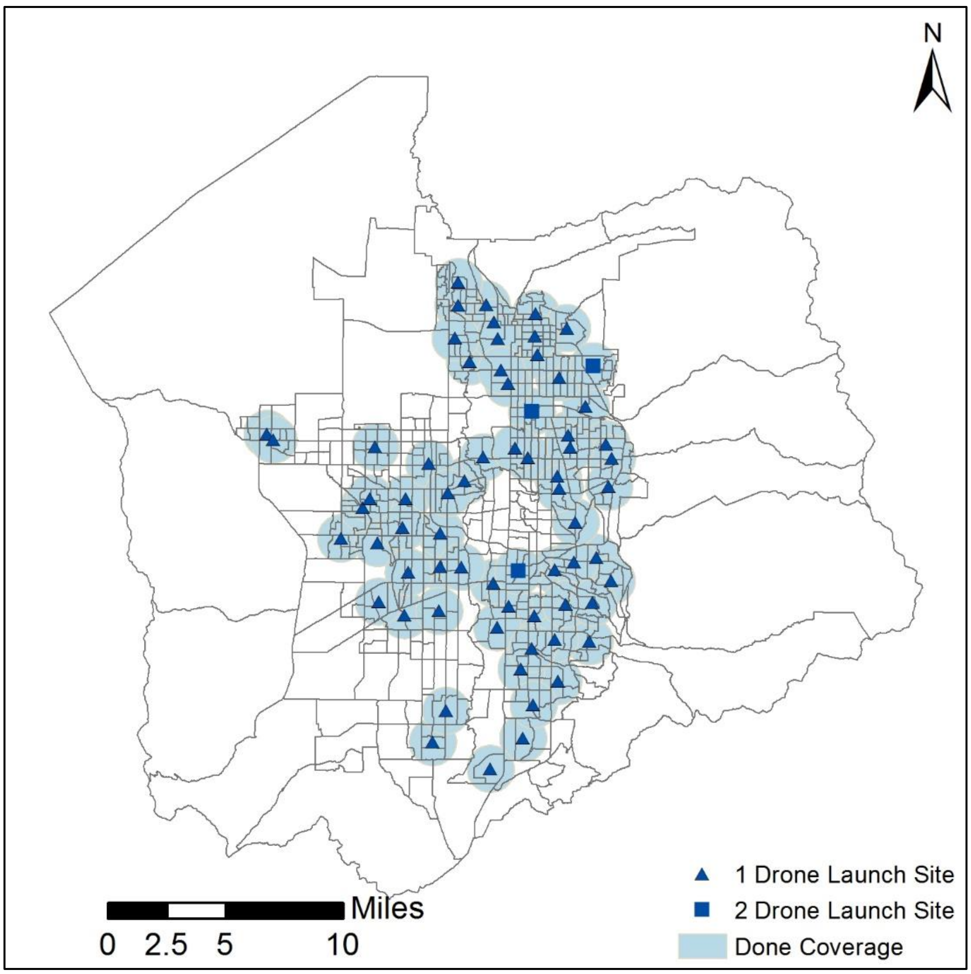

Figure 5.5 Identified spatial configuration of drones using BCLP-CC when $w_b = 0.2$.

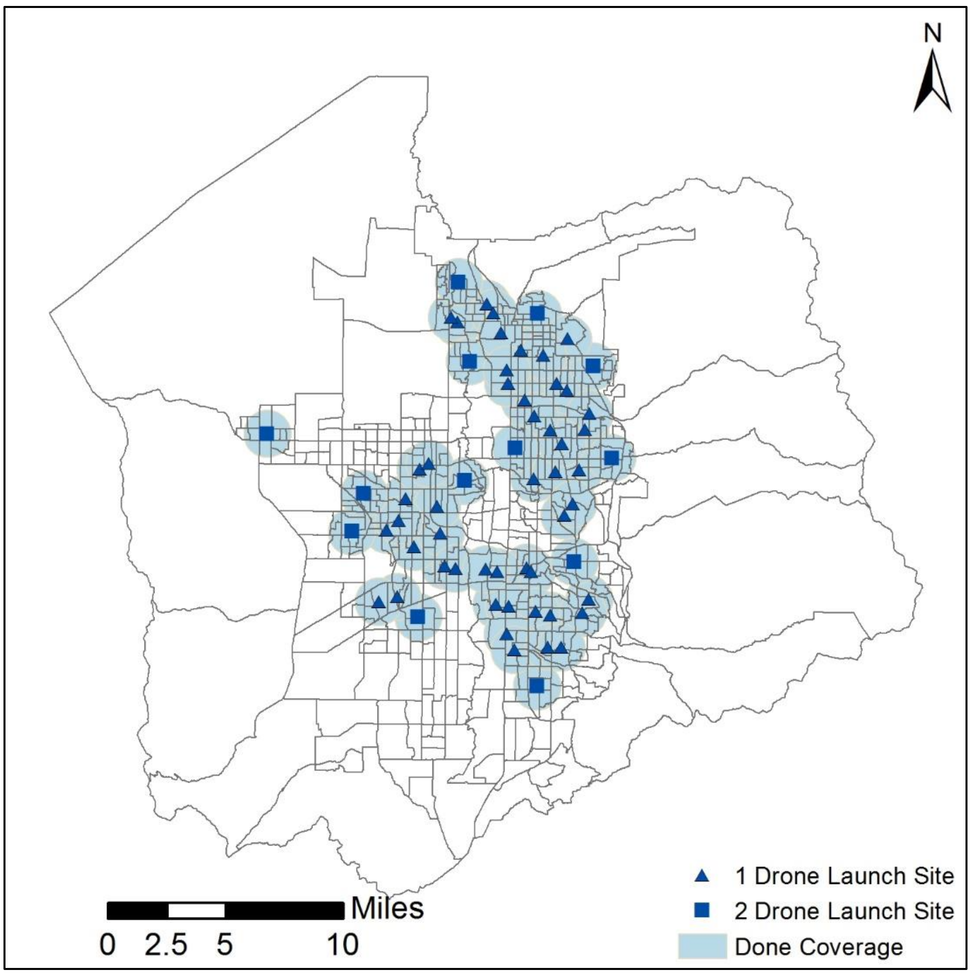

Figure 5.6 Identified spatial configuration of drones using BCLP-CC when $w_b = 1.0$.

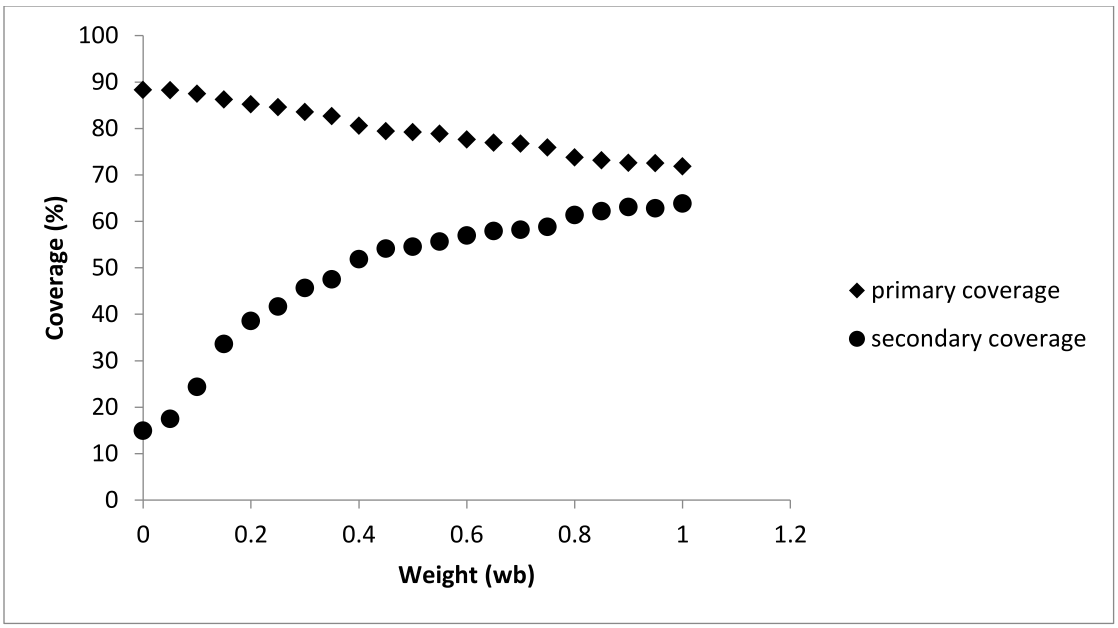

Figure 5.7 Coverage trade-off curve when p = 50.

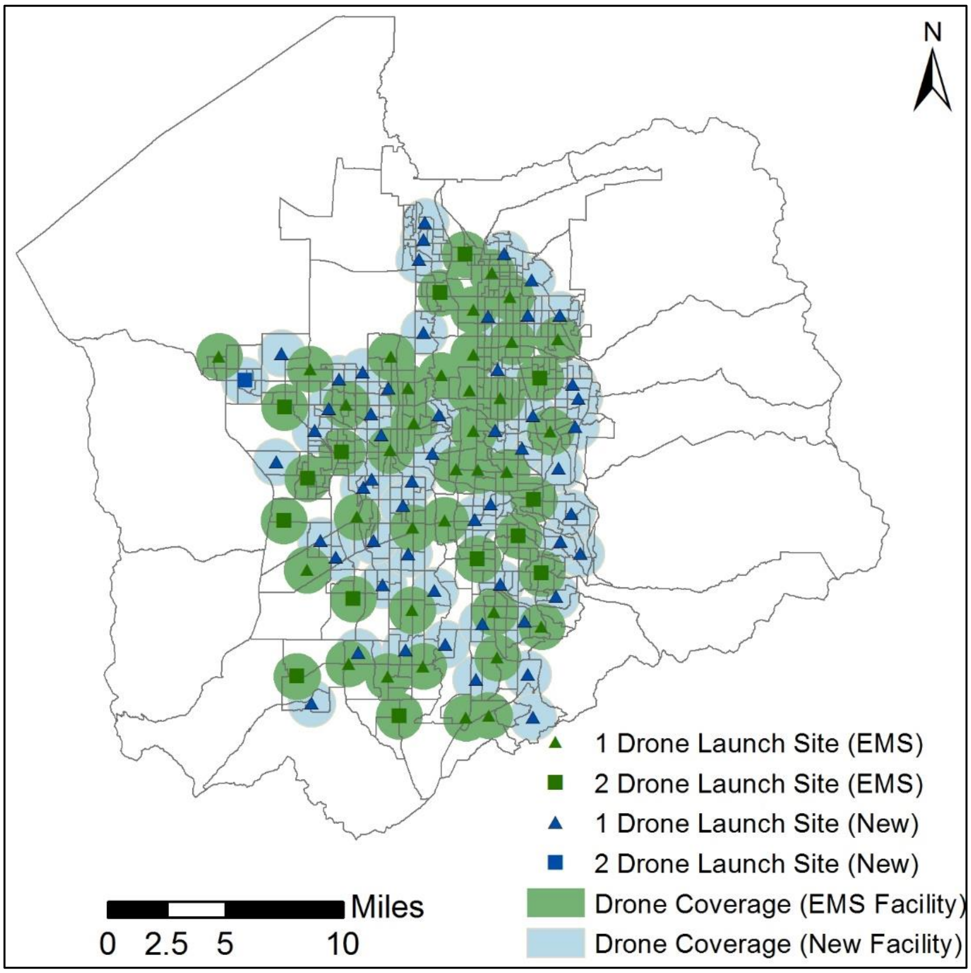

Figure 5.8 Identified population-based spatial configuration of drones using BCLP-CCCI.

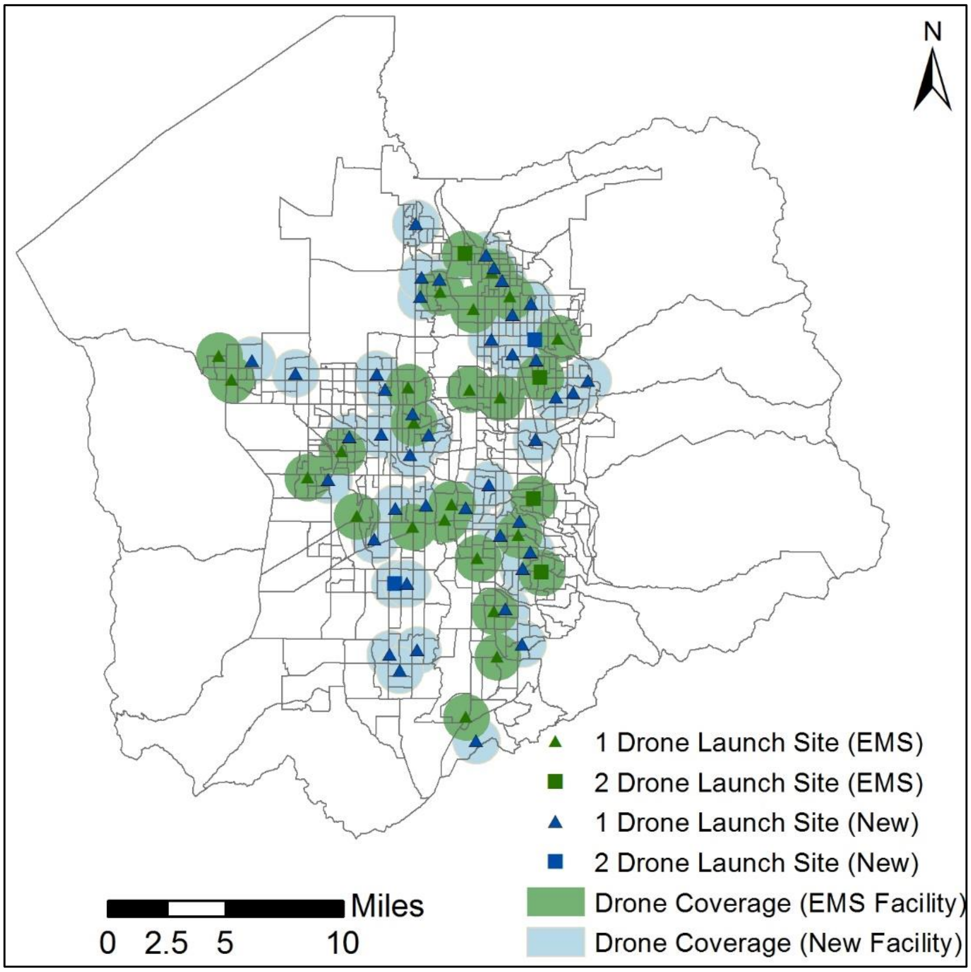

Figure 5.9 Identified incident-based spatial configuration of drones using BCLP-CCCI.

CHAPTER 6

DISCUSSION AND CONCLUSIONS

This study examined the spatial and temporal distribution of out-of-hospital cardiac arrests in Salt Lake County over a four-year period. The relationship between several factors including emergency medical service (EMS) response time, the aid provided by EMS, and the demographics of the patients were analyzed. In accordance with these findings, a new location model, the *backup coverage location problem with complementary coverage* (BCLP-CC), was developed to locate a network of medical drones to reduce EMS equipment travel times. Finally, this model was extended and applied to find the most cost-effective configuration of medical drones so that at least 90 percent of the demand is reachable within one minute.

Results suggest that in accordance with most literature, fast EMS response times are critical to sudden cardiac arrest (SCA) survival (see Figures 5.1 and 5.2). As shown in Figure 3.2, travel delays in Salt Lake County are centered around 5 minutes, which is well within most guidelines. However, due to the significant correlation between response time and SCA survival there is definitely room for improvement.

Emergency management systems must account for the fact that resources will not always be available when distress calls come in. It is important that additional resources and facilities can provide some level of service in these situations. This also applies to new upcoming technologies such as medical unmanned aerial systems (UAS). To support the location decision making of medical drones, a new location model, the *backup coverage location problem with complementary coverage* (BCLP-CC), which aims to maximize both the primary and backup coverage provided by a set of launch sites while explicitly taking into account the continuously distributed demand was developed. Results show that the BCLP-CC can significantly improve backup coverage with minimal loss of primary coverage. Since the BCLP-CC model is less computationally complex than related models, it was able to be solved with reasonable computational efforts on a standard desktop workstation. To fulfil the final objective of this study, a cost-effective network of medical drones, the BCLP-CC was extended to the *backup coverage location problem with complementary coverage and capital improvement* (BCLP-CCCI) to work with multiple types of facilities with differing costs in order to select the most cost-effective configuration of medical drones. It was shown that, as result of the spatial distribution of demand, covering historical incidents with a new drone network had significantly lower implementation costs than covering the population. Therefore, in the future, it may be best to consider a single hybrid demand that incorporates both incidence rates and population.

There are several issues that require further discussion and research. First, this study focuses solely on reducing equipment travel time. There are many other important EMS times which were not incorporated. For example, the time it would take for an automated external defibrillator (AED) delivered by a drone to reach a patient varies significantly based on small-scale locations (e.g., road-side vs. a high-rise building). By incorporating historical EMS delays when calculating the drone service areas, future studies may be able to create more realistic coverage scenarios.

Second, although new launch sites and existing EMS facilities were used to determine the best locations for deploying medical drones, there may be other suitable launch sites such as hospitals, urgent care centers, and private buildings. It was also assumed that all potential new launch sites are in valid locations which may not be the case as they may be located in wetlands, on roadways, or in other restricted areas. In future studies, this could be overcome by integrating high-resolution land-cover data, aerial imagery, or parcel data.

Third, the drones are assumed to fly in straight-lines (Euclidean distance) at top speed to patients. However, there may be buildings, trees, restricted airspace and other aircraft to navigate around. Some initial testing shows that incorporating trees and buildings derived from LiDAR data could reduce the service range of a single drone by around 10 percent, however a comprehensive study remains to be done.

Fourth, due to the fact that most cardiac arrests occur at home (de Vreede-Swagemakers et al. 1997), this study ignores the placement of fixed-location AEDs. These are commonly found in schools, large buildings, and public facilities. In certain situtations it may be quicker to locate a local AED than to rely on a medical drone to deliver one. In the future, service areas for these fixed-location AEDs could be derived using the average walking or running speed and detailed building layouts. The BCLP-CC could then be extended to incorporate these additional available resources.

Fifth, it is worth noting that although a quick EMS response and defibrillation are critical for cardiac arrest survival, there are many other factors that contribute to survival such as the time of patient discovery, whether cardiopulmonary resusciation (CPR) was performed by bystanders, the fitness of the patient, and the age of the patient.

Sixth, this study does not take into account several fixed and start-up costs for implementing an AED-enabled drone network. Dispatch centers will have to be updated to connect to the drone network. Dispatchers and EMS staff will need new training in order to sucessfully use the medical drones. There will be additional maintaince costs such as replacing or repairing drones. It is crucial for planners to account for these additional costs.

Finally, this study assumes that the general populace accepts medical drones as a significant technological and medical advancement and embraces using these technologies. There are many privacy concerns regarding drones, as a technology, which must be considered. In addition, the possibility of theft or destruction of medical drones must also be accounted for.

Despite these limitations, this research developed a computationlly-efficient, cost-effective spatial optimization approach to appropriately site a network of medical drones that can reduce life-saving equipment travel times for victims of cardiac arrest. Given the growing need to use drones in emergency services, more applications of this approach could be anticipated in future. For example, the BCLP-CC(CI) could easily be extended and applied to many other metropolitan areas to examine the needs for medical drones. In addtion, the BCLP-CC(CI) is not limited to drone network implementations and it could be used for a wide variety of applications.

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